Recognize Faces across Multi-View Videos and under Varying Illumination, Facial Expressions

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***Abstract*—**Recognition human faces across videos is simple when we find the frontal view of the person but it's a challenging task across other views. Also recognizing human faces across varying illumination and facial expressions under un-controlled environment is equally challenging task. In this paper we have made and attempt to solve these problems by developing three novel techniques to recognize human faces from multi-view videos, varying Illumination and Facial Expression. All the three developed systems are validated on standard publicly available databases. Recognizing human faces images from multi-view videos is developed using Spherical Harmonics and Radial Basis Function (RBF) kernel Technique, recognizing human faces across varying light conditions is developed by combining Local Binary Pattern (LBP) and Support Vector Machine (SVM), andrecognizing human faces across varying facial expressions is developed by combing Linear Discriminant Analysis (LDA) and Hidden Conditional Random Fields (HCRF).

***Keywords*—**Spherical Harmonics, Radial Basis Function Kernel, Local Binary Pattern, Support Vector Machine, Hidden Conditional Random

I. INTRODUCTION

Recognizing human faces and across multi-view videos and under varying illumination, facial expressions is a very challenging task. In traditional recognition techniques input image containing the best detection is cropped to a square region around the face, and is then position estimates of eye and mouth corners are computed [1]-[2]. An approach for detecting the face with better detection rate for multi-view, non-frontal and frontal faces is proposed in [3]. This approach consumed less time and worked well even if the background features were poor. Here, cascaded detectors of appearance based methods and skin feature were combined to get better performance results. Segmentation of skin color was based on YCbCr, HSV and RGB color spaces. YCbCr and HSV color spaces helps in separating color and intensity information[4]-[6]. Haar features obtained at each stage of cascade, image size and scale factor of detector are the factors that influence the time taken in detecting all faces in the image. Accuracy and precision can be further improved by using the methods such as support vector machine and varying the AdaBoost. Another method for detecting the faces in the image automatically by developing the previously proposed Viola-Jones method is given in [5]. The Viola-Jones method cannot discriminate faces from non faces and required many AdaBoost iterations to decrease the false positives. To the Viola-Jones method plethora of various feature sets is boosted to detect the faces in the image. Like this by using the diversified features, performance of the AdaBoost approach is strengthened in detecting the faces in the image. Detection of skin color regions using YCbCr color space is given in [7]. YCbCr color space can effectively segment the skin color. In the next step four connected components were obtained and region on the face consisting of triangular feature was found. Using Float Boost based classifier; it was determined whether the region discovered in the previous step consists of face.Automatically detecting multi view face and multi view pose is presented in [8]. For building the face detector and pose estimator, modified learning methods are used. The method uses five modules. After the preprocessing stage coarse face detector is used which helps in cancelling the non-face regions. Now the obtained facial patches are classified in to three clusters. In the fine level, modules such as fine face detector, post processing and fine pose estimator module is included which helps in increasing the performance. Since the sub regions of the image are less sensitive to lighting and geometry variations the face detector considers sub regions of image than global images.For capturing best front view of a person is given in [9],this approach tries to recognize the face using the geometric features of the image. Curve Edge Maps

(CEMs) are used in representing the face. CEMs are the set of polynomial curves containing convex region. Face CEMs driven by histograms of intensities is matched with face CEMs driven by histograms of relative positions to perform the face recognition function.

A method for recognizing faces under varying illumination conditions is presented in [6]. Methods used in this approach are Support Vector Machines (SVM), Eigen face method and Face edges extraction method. Initially the illumination conditions on the face are cancelled, to obtain a binary image with pixel values 0 or 1. In the next step using the pixel value 0, in binary image a fuzzy face model is constructed. Using fuzzy approach face in the image is detected. Advantage of this approach is that face of the person with any skin color can be detected. An approach for facial detection in varying illumination conditions and whose location is not known is given in [4]. The illumination conditions were cancelled to detect the faces instead of using skin color. After the various illumination conditions are cancelled in the original image, binary image is obtained. Two methods are used in this approach - fuzzy logic based method and Eigen face based method. Since the methods used in this approach to detect the faces is completely independent of information regarding skin color, even in dark environment any kind of skin color can be detected. After detecting the face aspects, feature based method is combined with Eigen face method to get better results. The defect of Eigen face method is illumination dependency problem, this problem can be solved by using the binary images and we need not have to undergo illumination normalization to solve the illumination dependency problem. It is found that Eigen based method performs better than fuzzy logic based method.A novel method for detecting the faces retrieved from a video surveillance system is presented in [9]-[15]. While receiving the images from video it undergoes several challenges with respect to resolution, motion blur, illumination and occlusion. Multiple cameras captures the different images of the person face uniquely which tends to self- occlusion problem. To track the faces from multiple camera Cylinder Head Models (CHMs) methodology is used. One of the main advantages of CHMs is the recovery of full motion parameter. Another technique for recognizing the face in the noisy video which is affected is presented in [16] where non-rigid face tracking approach is used, which makes use of general form of facial features. Dealing recognition of faces in the camera which captures multiple frames in an uncontrolled condition is presented in [17]. If the face is not localized properly it may lead to scale and alignment variations, this problem was solved by retrieving a probabilistic face model to create an ideal face. This method works efficiently with any given variations in geometric alignment, sharpness, head pose and shadows.

Using face tracking in software, a facial tracking based head movement control system is developed in [18]. By combining hardware and software, the simple face tracking method is further enhanced into a wide tracking region. Various algorithms and methods like Haar-like face detection algorithm, camshift face tracking algorithm and fuzzy logic controller have been explored, which reveals that the proposed system is able to improve and improve the overall monitoring system [19]-[30].An efficient SVM approach is proposed for recognizing human faces that are embedded within digital cam recorders, in [31]-[40]. Under non-uniform illumination conditions and complicated backgrounds, the proposed face recognition system performs wonderfully on face images with various sizes. The automatic face recognition and detection system contains both detection and recognition phases [41]-[46]. Detection Phase employs the lighting normalization function and isosceles triangle approach for accurate facial region detection. The recognition phase employs the SVM classification approach as a unique signature for face recognition. Real-time face detection in a video sequence is given in [47], which allowed the analysis of faces in the video sequence using highly time consuming and highly accurate method of face detection at the expense of small-time latency. Barring time complexity, the developed algorithm with the tracking procedure exhibit the same properties as that of the procedure that performs face detection in every frame in parts, where the detector is successful [48]-[53]. Section 2 presents three novel techniques to recognize faces under multi-view videos, varying illumination and facial expression. Section 3 presents the Results and Discussions. Section 4 draws the Conclusion.

II. PROPOSED SYSTEM

In this paper an attempt has been made to work on three difficulties in recognizing faces under multi-view videos, varying illumination and facial expression.

A. Detecting and Recognizing Face Images from Videos using Spherical Harmonics and RBF kernel Techniques

The video is converted into frames, which are considered as images. Here we have two stages- training stage and testing stage. Training stage consists of images from database whichare not affected by any noise and whose face regions aredefined clearly, whereas testing stage consists of images obtained from video which may have noise and whose face regions are not defined. Pre-processing is applied to the video frames to remove noise using median filter. Then face region in the frame is detected and is masked. Based on the position of the face in the frame the face region is detected throughout the video. Histogram of Oriented Gradients (HOG) features are obtained from images in both phases. Spherical Harmonics is applied to the images in both the phases for recognition. The distance between the train image feature and the test image features were calculated. The image that is having the minimum distance is retrieved from the database.Modules for Detecting and Recognizing Face Images from Videos using Spherical Harmonics and RBF kernel Techniques

- **Pre-processing:** The video is first converted into frames, where each frame is considered as image. Noise in the image reduces the quality of the image. In order to improve the quality of the image, median filter is used for filtering. The median filter considers all pixels of an image and by considering one pixel as reference, it observes the nearby pixel values, arranges all the pixel values in ascending order, and finds the median value.

The reference pixel value is replaced with the newly obtained median value. This process continues for all pixels.

- **Face Detection:** The face is detected from the frame using the vision cascade operator which identifies the face region in the image. It gives the x and y position of the face images. The position of the detected face image is taken and a rectangle is drawn at the particular location.
- **Face Masking:** The face region is then masked based on the detected face region. The region which is detected as face is taken and the particular region is marked separately. Areas other than the face region are blackened and face region alone is masked. This will be helpful in the correct recognition of the face images in later stages.
- **Tracking:** The position of the face regions at each frame is updated each time and the person is tracked throughout the video. Every time the face region is identified by analyzing the movement of the person in the consecutive frame. The position is updated each time so that the system is trained to identify the movement of the person in the frame and all these times the position of the rectangle is moved according to the movements identified in the frame.
- **Recognition:** Feature Extraction is done using HOG and these features are applied to Spherical Harmonics for recognition. The distance is calculated between the test feature and the train feature. The image corresponding to the feature having minimum distance is retrieved from the database.
- **Spherical Harmonics:**The spherical harmonics Ylm (ϴ, ø) represent the angular part of Laplace's equation resolution in round coordinates. Here, ϴ is taken as the co-latitudinal coordinate with ϴ ϵ (0, Π), and ø as the longitudinal coordinate with ø ϵ (0, 2Π). Spherical harmonic differential equation is satisfied by the Spherical harmonics, which is presented by the angular part of Laplace's equation. Spherical Harmonics are represented as

$$Y_l^m(\theta,\emptyset) = \sqrt{\frac{(2l+1)(l-m)!}{4\pi(l+m)!}}P_l^m(\cos\theta)e^{im\emptyset} \qquad (1)$$

Where, $P_l^m(x) = (-1)^m(1-x^{2)}{}^{\left(\frac{m}{2}\right)}\frac{d^m}{dx^m}P_l(x)$(2)

Where, $P_l(x) = \frac{1}{2^l l!}\frac{d^l}{dx^l}(x^2-1)^l$(3)

Here m is order, l is degree

- **RBF kernel**: In machine learning, a well-known kernel function called the radial basis function kernel (RBF), is used in classification of support vector machine. RBF kernel on x and x' is defined as

$$K(x,x') = \exp\left(-\frac{\left|\left|x-x'\right|\right|^2}{2\sigma^2}\right)(4)$$

Where |(|x-x^' |)|^2a squared Euclidean distance and σ is is a free parameter.

- **Bhattacharya Distance**: The similarity of two discrete or continuous probability distributions is measured using the Bhattacharya distance, which calculates the amount of overlap between two samples or populations. Bhattacharya coefficient of two distributions p and q in the same domain x is defined as,

$$\mathrm{BC}(\mathrm{p},\mathrm{q}) = \sum_{x\in X}\sqrt{\mathrm{p(x)q(x)}}(5)$$

And Bhattacharya difference can be calculated as,

$$D_B(p,q) = \frac{1}{4}\ln\left(\frac{1}{4}\left(\frac{\sigma_p^2}{\sigma_q^2}+\frac{\sigma_q^2}{\sigma_p^2}+2\right)\right)+\frac{1}{4}\left(\frac{(\mu_p-\mu_q)^2}{\sigma_p^2+\sigma_q^2}\right)(6)$$

Where, DB (p, q) is Bhattacharya distance between class p and class q.

σp represent the variance of pth classes, µp gives the mean of pth class. p and q are the two different distributers System architecture of detecting and recognizing face images from videos using Spherical harmonics and RBF kernel techniques is shown in Fig.1.

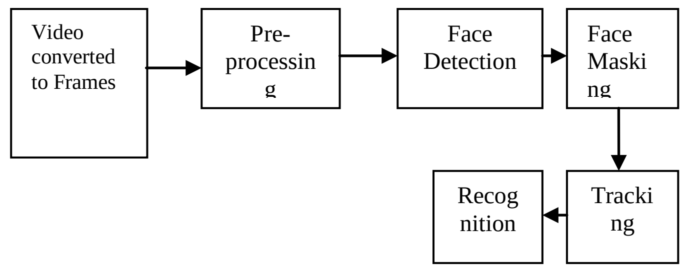

Fig.1. System Architecture of Detecting and Recognizing Human Faces from Videos using Spherical Harmonics and RBF kernel Techniques

B. *Recognizing Images across Varying Lighting Conditions using LBP Feature Extraction and SVM Classification Techniques*

To recognize images across varying lighting conditions, we sharpen and enhance the blur image with different lighting conditions which is a test image and images in database for performing pre-processing using Gaussian filter. Then we extract features using LBP feature extractor. We calculate the weighted mapping for the test and the dataset images. After the feature set has been computed for each pixel, this feature will be passed to the SVM classifier. The classification stage has two main parts- a training stage and a testing stage. In training stage features of images in dataset are divided in to different classes and in testing stage, based on the features of test images, the classifier decides to which class of the dataset the input image belongs to.Modules for Recognizing Images across Various Lighting Conditions using LBP Feature Extraction and SVM Classification Techniques:

- **Pre-processing**: In pre-processing method Gaussian filter is used to remove unwanted noise from the input images. The Gaussian filter is a nonlinear digital filtering technique normally used in removing noise. Noise reduction is an important step in any recognition techniques. Gaussian filter perform smoothening of the image without having more effects on edges of image which are the major characteristic of an image i.e. it preserves the edges even after smoothening.

- **Normalization**: Normalization is a process where the pixel intensity values of a range changes. Illumination variation caused by changes in sources of light at different positions and various intensities causes large variations. To overcome this problem we obtained a new method of performing image normalization. This method removes shadows and secularities from images. All shadowed regions are given a uniform color and then it eliminates the soft shadows and secularities and thus creates an illumination invariant copy of the original image.
- **LBP Feature Extraction**: LBP is a texture descriptor which can be used to recognize faces. Each pixel of image will be assigned a label by this operator. Taking center pixel as reference it assigns binary values to pixels surrounding it. It assigns value 1 if the pixel value is greater than center pixel value else value 0. Combining these 0s and 1s we get a binary value. We convert this binary value to a decimal number and the resulting decimal number is given as label to the center pixel. This process is repeated throughout the image. Later based on these labels classification is performed.
- **Recognition**:SVM classifier is used to recognize images. SVM classifier classifies two classes by drawing a hyper plane between two classes. The hyper plane is drawn such that it is at a equal distance between the features of both class which is close to other group and must have a maximum distance between the features. Let us assume that first the classifier classifies two classes as class 1 and class 2 by drawing a hyper plane between them. Now if a new test case is entered this classifier decides which class does this test sample lies by observing the feature placement. If majority of features of new test sample lies on one side i.e. class 1 side of hyper plane then this test sample belongs to class 1. If it lies on other side i.e. class 2 of hyper plane then it belongs to class 2. After classifying we analyze about our classification. We analyze if there is any misclassification in our result. Then we find accuracy of our system. The system architecture for recognizing images across obscure and various lighting conditions using LBP feature extraction and SVM classification techniques is shown in Fig.2.

C. *Recognizing Images across Varying Facial Expression using Linear Discriminant Analysis and Hidden Conditional Random Fields*

To recognize images across varying facial expressions, we use Stepwise Linear Discriminant Analysis (SWLDA) coupled with Hidden Conditional Random Fields (HCRF) for a sequence-based Facial Expression Recognition(FER) system. Though SWLDA has been used in many different areas before, it is for the first time that it is being utilized as a feature extraction technique in an FER system. The purpose of using SWLDA as a feature extraction technique is to extract the localized features from faces that the previous feature extraction techniques were limited in analyzing.Modules for Recognizing Images across Varying Facial Expression using Linear Discriminant Analysis and Hidden Conditional Random Fields:

- **Stepwise Linear Discriminant Analysis:**Reduction of Dimension by discriminating feature extraction is based on maximizing total data scatters and minimizing the variance within classes. High misclassification rate is obtained by merging the feature values for six classes. For visualization purpose the first three features were picked up to create it. This work employs SWLDA which is easy and low cost.
- **Hidden Conditional Random Fields:**In the existing approach HCRF uses diagonal co-variance Gaussian appropriations in the feature function and does not ensure the convergence of its parameters to some particular value at which the conditional probability is displayed as a mixture of ordinary density function due to this existing HCRF loses a considerable amount of data. To overcome this disadvantage full co-variance Gaussian distributions in used for feature functions at the observation level.
- **Classification:** Artificial neural networks (ANNs) and Support Vector Machines (SVM) are used to classify different facial expressions. ANN has adequate capacity to differentiate fundamental relationships but it requires long time to train.In SVMs using indirect approach observation probability is calculated. Hence SVMs essentially ignore transient conditions among video frames and each frame is expected to be independent from the rest which is shown in Fig. 3.

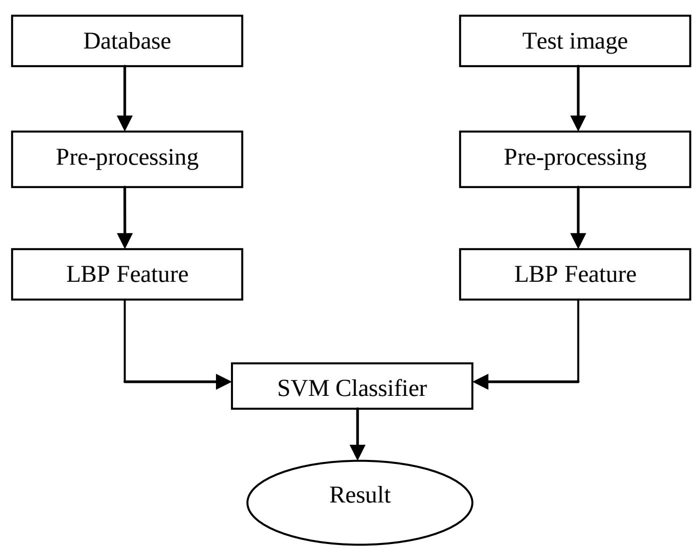

Fig.2 System Architecture for Recognizing Human Facesacross Varying Lighting Conditions using LBP Feature Extraction and SVM Classification Techniques

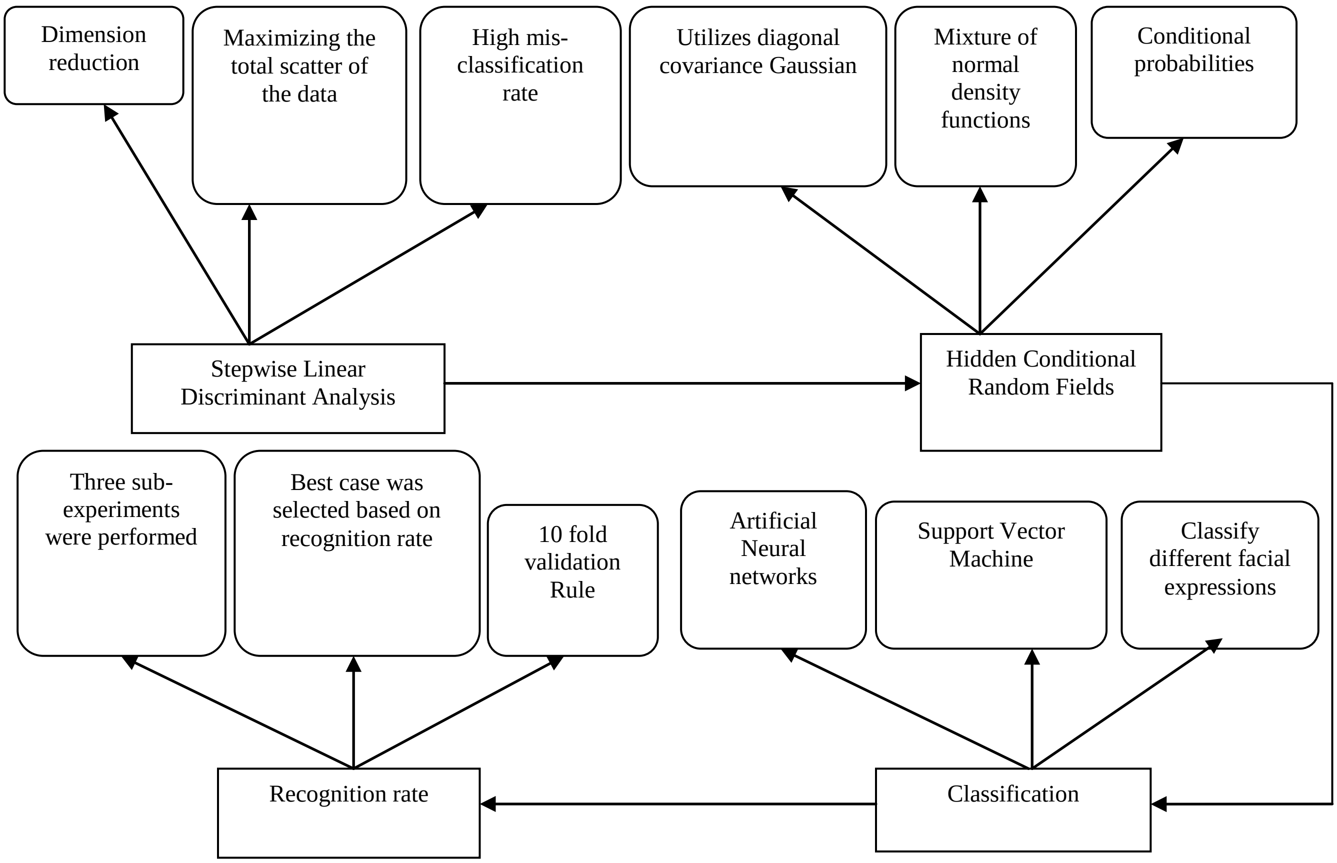

Fig.3System Architecture for Recognizing Human Faces across Varying Facial Expressions Linear Discriminant Analysis and Hidden Conditional Random Fields

III. RESULTS AND DISCUSSIONS

A. Detecting and Recognizing Face Images from Videos using Spherical Harmonics and RBF kernel Techniques

Step by step implementation for Detecting and Recognizing Face Images from Videos using Spherical Harmonics and RBF kernel Techniques is shown in Fig.4.

A comparative study of various face detection and recognition techniques across videos on three different videos is tabulated in Table 1.

Table 1 indicates the proposed Detecting and Recognizing Face Images from Videos using Spherical Harmonics and RBF kernel Techniques gives the best recognition rate.

B. Recognizing Images across Varying Lighting Conditions using LBP Feature Extraction and SVM classification Techniques

Step by step implementation for Recognizing Images across Varying Lighting Conditions using LBP Feature Extraction and SVM classification Techniques is shown in Fig.5. A comparative study of various face recognition techniques under varying lighting conditions on Yale B database is tabulated in Table 2.

Table.1. Face Recognition Rate across videos

Author	Method	Database	Recognition Rate (%)
PojalaChiranjeevi, *et al* [38]	Personalized Appearance Models	CK+	75%
Chao Xiong, *et al* [39]	Gabor Feature, LBP Feature, SIFT (Scale Invariant feature Transform) and SVM	CK+	68.87%
Sujitha Martin, *et al* [40]	Automatic Machine vision , Gaze zone estimation	CK+	71%
Himanshu S. Bhatt, *et al* [41]	Clustering, Re-Ranking and Fusion	CK+	23.8%
Spherical Harmonics and RBF kernel Techniques (Proposed		CK+	**98%**

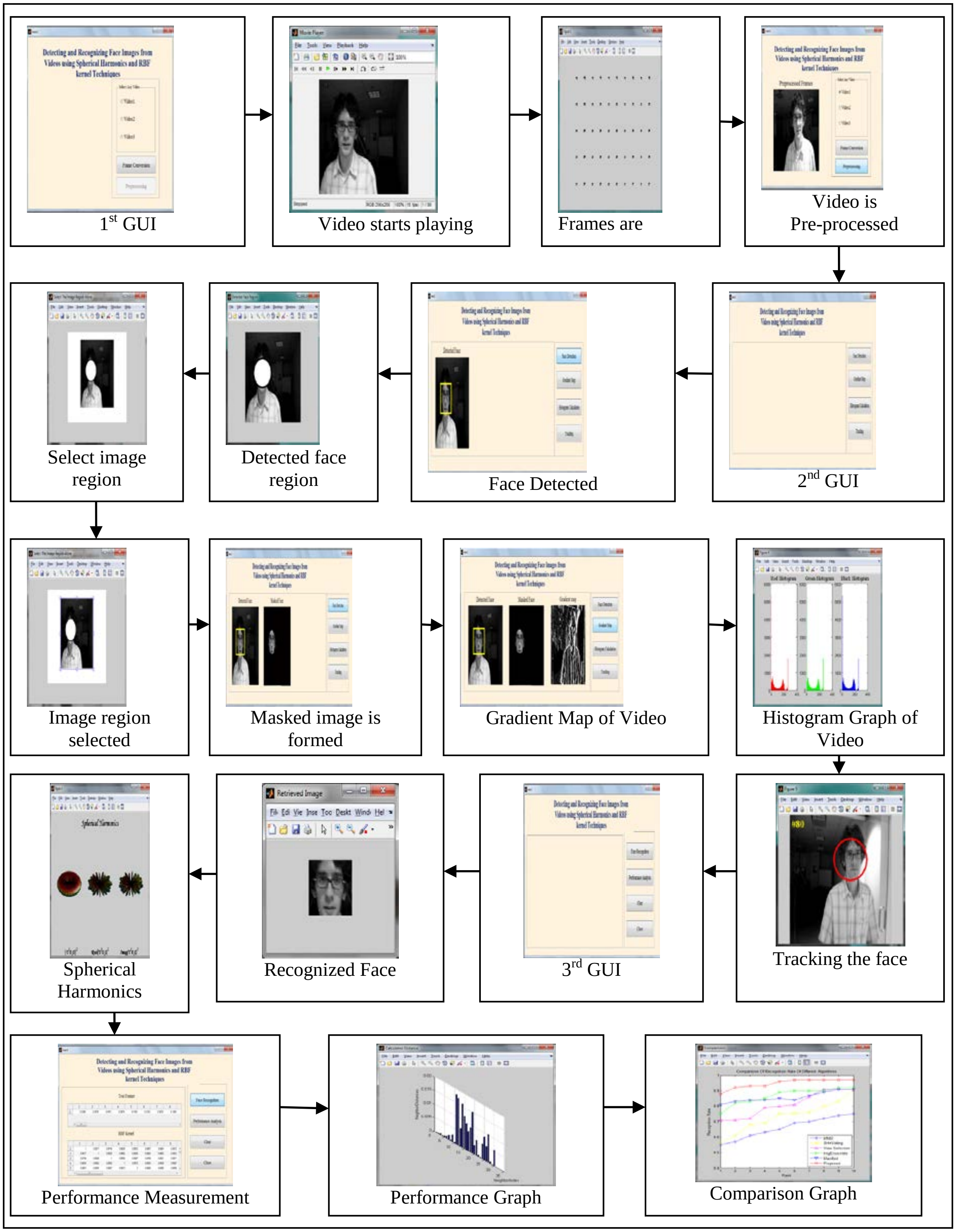

Fig.4. Detecting and Recognizing Face Images from Videos using Spherical Harmonics and RBF kernel Techniques

Table.2. Face Recognition Rate under Varying Lighting Conditions

Author	Method	Database	Recognition Rate (%)
AbhijithPunnappurath, *et al* [25]	TSF (Trading Support Facility) model	Yale B	76.27%
Chi Ho Chan, *et al* [42]	Multiphase Local Phase Quantization (LPQ), kernel fusion of multiple descriptors	Yale B	87%
Zhengwu Zhang, *et al* [43]	Riemannian Framework	Yale B	65%
ZeynepYucel, *et al* [44]	Gaussian Process Regression, Neural Networks, Saliency Schemes	Videos	80%
LBP Feature Extraction and SVM Classification (Proposed System)		**Yale B**	**100%**

Table 2 indicates the proposed Face Recognition Technique using LBP Feature Extraction and SVM Classification gives best recognition rate on Yale B database.

C. *Recognizing Images across Varying Facial Expression using Linear Discriminant Analysis and Hidden Conditional Random Fields*

Step by step implementation for Recognizing Images across VaryingFacial Expressions using LDA and HCRF Techniques is shown in Fig.6.

A comparative study of various face recognition techniques under varying Facial Expressions on JAFEE database is tabulated in Table 3.

Table.3. Face Recognition Rate under Varying Facial Expression

Author	Method	Database	Recognition Rate (%)
J. Kalita and K. Das [50]	Eigenvector based distributed features and Euclidean distance based decision making	JAFEE	86%
F. Long, T. Wu, J. R. Movellan et.al [51]	Spatiotemporal Features by using Independent ComponentAnalysis	JAFEE	74%
M. Z. Uddin, T.-S. Kim et.al [52]	Optical Flow andHidden Markov Model	JAFEE	92%
W. Gu, C. Xiang et.al [53]	Radial Encoding of Local Gabor Features and Classifier Synthesis	JAFEE	96%
LDA and HCRF (Proposed System)		JAFEE	**100%**

Table 3 indicates the proposed Face Recognition Technique using LDA and HCRF gives best recognition rate on JAFEE database.

IV. CONCLUSION

In this paper we attempted to develop three novel techniques for recognition of faces from Videos, under varying illumination and facial expressions. Detecting and recognizing face images from Videos is proposed using Spherical Harmonics and Radial Basis Function (RBF) kernel Technique. Recognizing images across Varying Lighting Conditions is proposed using Local Binary Pattern (LBP) Feature Extraction and Support Vector Machine (SVM) Classification Techniques and tested using Yale B database which consists of images across various lighting conditions. Recognizing images across VaryingFacial Expression is proposed Linear Discriminant Analysis (LDA) and Hidden Conditional Random Fields (HCRF).Techniques and tested using JAFEE database which consists of images across varying facial expressions. All the three proposed systems were tested across various existing state of the art techniques. From our analysis, it is found that proposed detecting and recognizing faces from videos using Spherical Harmonics and RBF kernel Techniques gives the best recognition rate of 98%. Recognizing faces across Varying Lighting Conditions using LBP Feature Extraction and SVM Classification gives the best recognition rate of 100% on Yale B database. Recognizing faces across VaryingFacial Expressions using LDA and HCRF gives the best recognition rate of 100% on JAFEE database.

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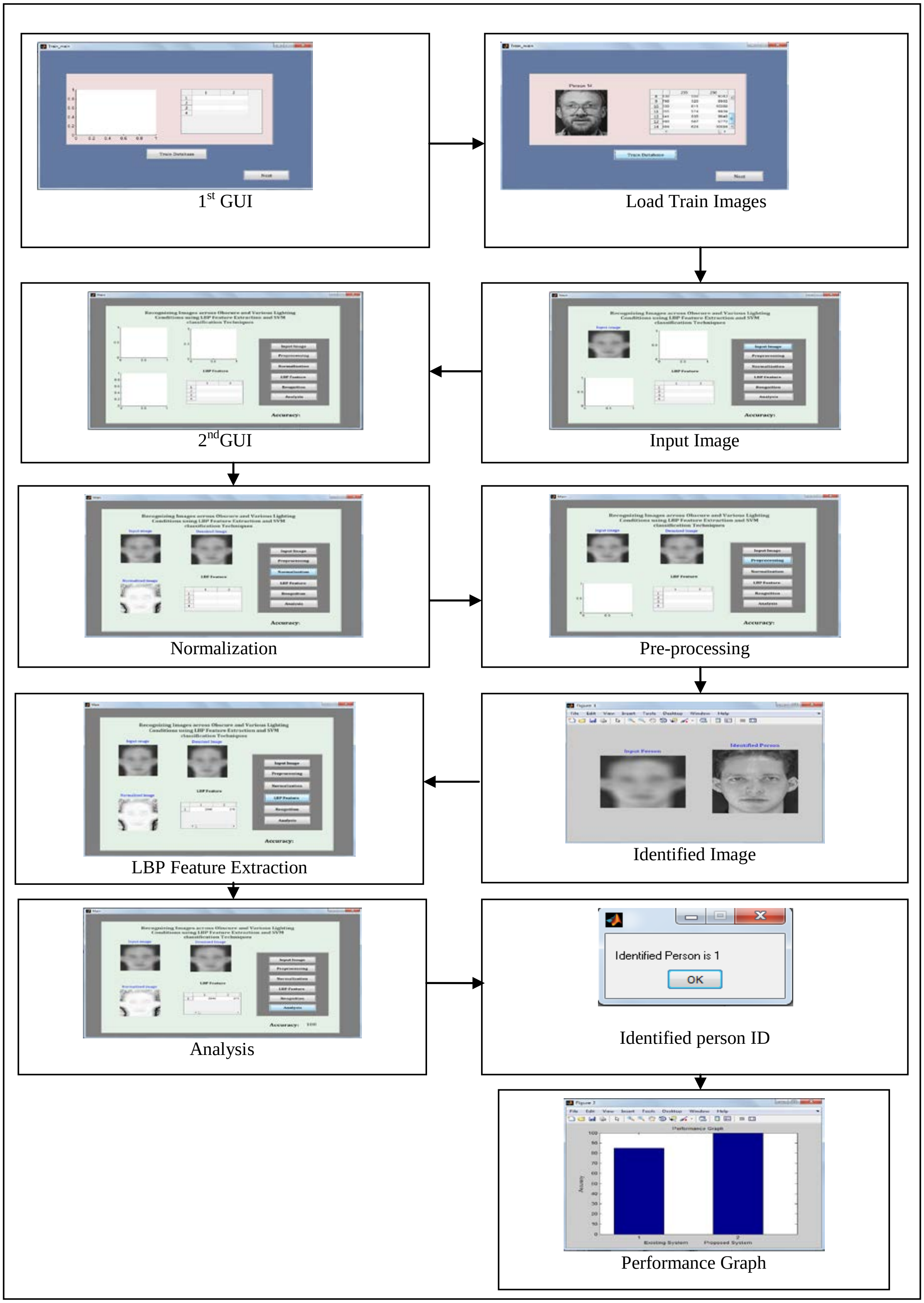
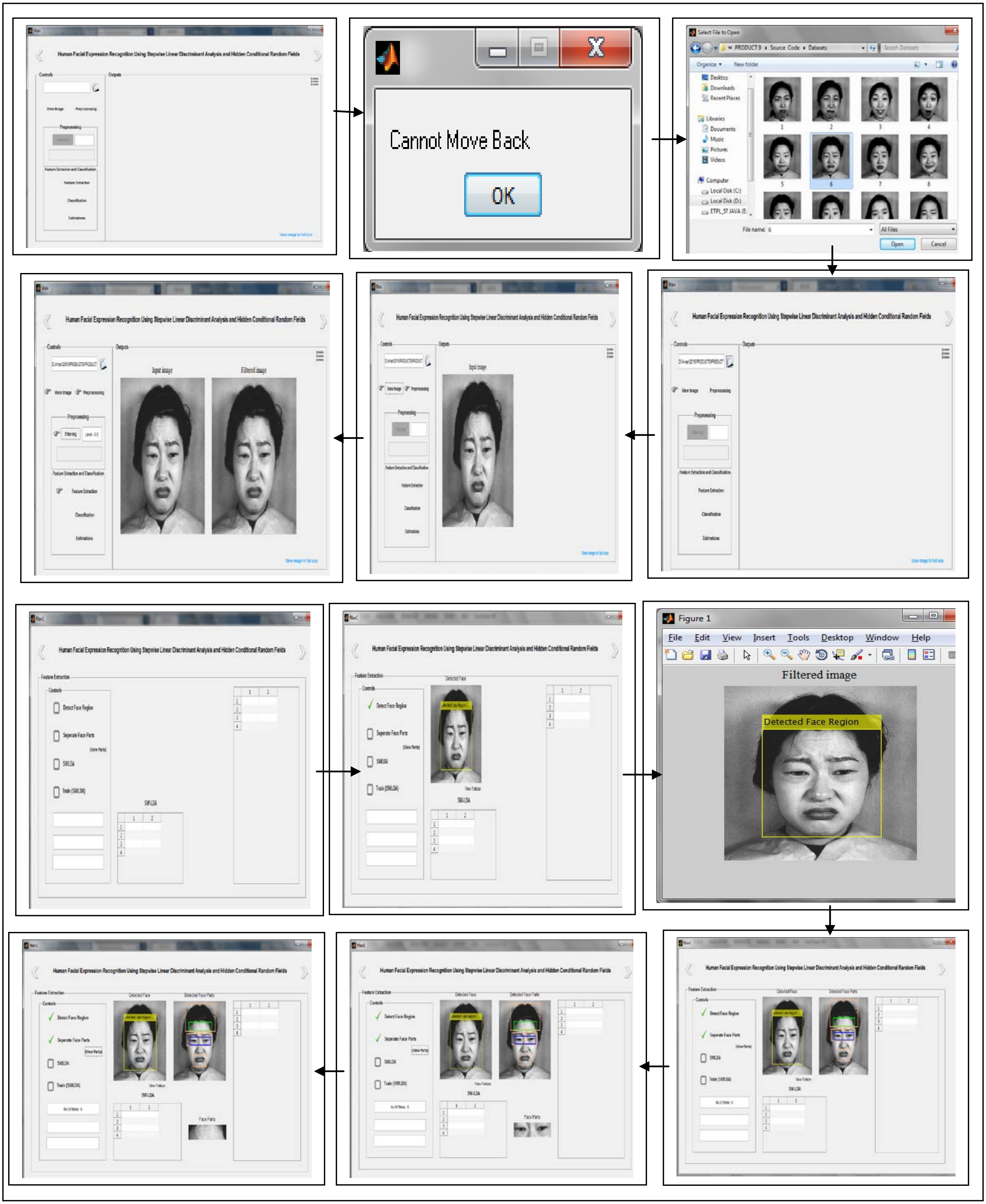


Fig.5. Recognizing Images across Varying Lighting Conditions using LBP Feature Extraction and SVM classification


Human Facial Expression Recognition Using Stepwise Linear Discriminant Analysis and Hidden Conditional Random Fields
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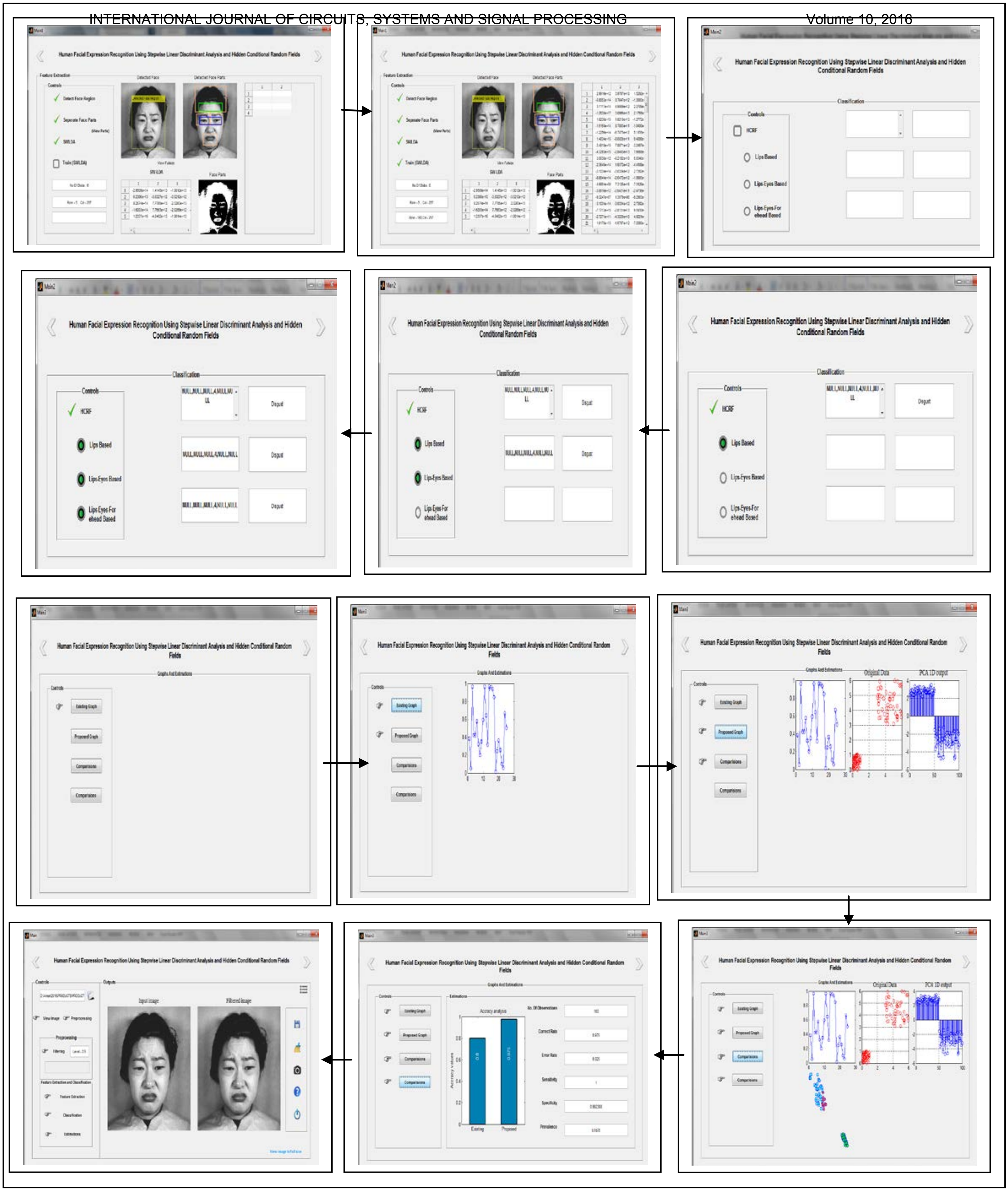

Fig.6. Recognizing Images across Facial Expressions using LDA and HCRF Techniques

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